


# Quantifying the effect of landscape structure on transport costs for biorefinery of agricultural and forestry wastes in Malaysia

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## Abstract

In the context of climate change, sustainable biorefinery helps to mitigate carbon emissions. This paper examines how landscape structure metrics allow us to better understand the economics of agricultural and forestry wastes transportation. To verify that the landscape structure plays a significant role, we quantify the fragmentation of various lignocellulosic feedstock in Malaysia, as a typical tropical country. Fragmentation is compared with the variations of truck size, transport distance, and biomass nature. We use GRASS GIS to develop a series of transport cost maps, to quantify feedstocks, to run various biomass transport simulations, optimize locations of potential biorefineries, and to compute landscape structure metrics. We find that the cost of 1 million tonnes feedstock increases by more than 4 USD/tonne for every added unit of edge density (fragmentation index). It also increases by more than 6 USD/tonne for every added 100 km of average transportation. The average truck size has also a strong nonlinear relation to the cost with −84 USD/tonne when changing from 3- to 26-tonne trucks. To our knowledge, this is the first paper to address simultaneously fragmentation with the other classical logistic factors in a tropical country like Malaysia. It has strong implications for policymakers: the importance of the landscape structure makes a seemingly abundant biomass not viable for biorefineries if too fragmented compared to a much less abundant one, but more concentrated. It also implies that in tropical countries where the landscape is typically very fragmented, multi-crop feedstocks could be considered for sustainable biorefineries.

## KEYWORDS

bioenergy, biomass, biorefinery, feedstock, landscape fragmentation, lignocellulose, residues, supply cost, transport cost, wastes

## 1 | INTRODUCTION

Sustainable biofuels and alternative fuels and energies may help to fight climate change, by mitigating CO<sub>2</sub> emissions.

When based on agricultural and forest biomass, their economics depend on the landscape structure of the feedstocks. Logistics and transport costs are particularly important for the supply costs of bioenergy feedstocks. The industrial location of

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biorefineries, their size, and economies of scale are critical. For second-generation biofuels, lignocellulosic wastes may come from forests and fields or processing units. The sourcing strategy is then also a critical point. The economy of second-generation biofuels is therefore a multifactorial question. Since Graham et al. (1997) and until very recently (Lee, Hashim, Lim, & Taib, 2019; Morato, Vaezi, & Kumar, 2019), a lot of papers tackled a few factors together through modelling or optimization with GIS. Almost all papers discuss various concepts of transportation distance, feedstock yield, and feedstock density or bulk volume. Perpiñá et al. (2009) were the first to discuss also sourcing strategies from multiple feedstocks, and Singh, Panesar, and Sharma (2010) were the first to discuss truck size. Only Gan and Smith (2011) and Torquati, Marino, Venanzi, Porceddu, and Chiorri (2016) address the resource fragmentation, where a resource is scattered throughout the landscape, and into many fragments. Our paper is the first to address simultaneously all these factors and to attempt to quantify the respective influences of resource fragmentation, and classical logistic factors such as biorefinery mill location, truck size, multi or single feedstock sourcing, yield density, and transportation distance.

In all the literature, only a minority of papers also address the same questions in tropical conditions: India (Singh, Panesar, & Sharma, 2008; Singh et al., 2010), Brazil (Uslu, Faaij, & Bergman, 2008), Mozambique (van der Hilst & Faaij, 2012), Malaysia (Lee et al., 2019), and Bolivia (Morato et al., 2019). Tropical conditions are very important to consider for second-generation biofuels, because of the high primary productivity of the vegetation under these latitudes. Yet, many tropical landscapes are very fragmented, especially in Southeast Asia (Fritz et al., 2015; Lesiv et al., 2018; Samberg, Gerber, Ramankutty, Herrero, & West, 2016). Our paper is also the first to explore the question of the spatial fragmentation in a tropical context, and in Southeast Asia.

A few works explore biomass economics in Malaysia, especially regarding location optimization (Chen, Ong, & Babin, 2017; Salleh, Gunawan, Zulkarnain, Shamsuddin, & Abdullah, 2019; Shafie, Othman, & Hami, 2020). Tan et al. (2018) optimize the location in Malaysia with assumptions that follow an American technical report. A few others study the potential of Malaysia for biomass energy (Griffin, Michalek, Matthews, & Hassan, 2014; Ozturk et al., 2017; Suzuki, Tsuji, Shirai, Hassan, & Osaki, 2017). None of these papers explore the question of fragmentation.

## 2 | MATERIALS AND METHODS

Peninsular Malaysia is an example of Southeast Asia landscape, with an intricate mosaic of land uses, and contrasted elevations. It comprises 13 million hectares of landmass. We used GRASS GIS (GRASS Development Team, 2018;

Neteler, Bowman, Landa, & Metz, 2012) open-source software on a 64GB RAM and 12-core computing station. The workspace was a 10,870 by 10,822 cell raster, where a pixel is approximately 0.4 ha ( $63 \times 63$  m). We obtained the land use layers from the Department of Agriculture Malaysia (2010). Our work considers distances, quantities of biomass, landscape patterns, and costs. CO<sub>2</sub> emissions are not considered directly other than through transport distances and costs.

### 2.1 | Transport costs

We obtained the effective driving network from the Malaysia–Singapore association of drivers (Malsingmaps, 2015). Any location could be a candidate site for biorefineries. But we simplified the possibilities by narrowing to the vicinity of 89 capitals of Peninsular Malaysia districts. We computed 89 transportation distance maps to the potential biorefinery locations. We computed them with GRASS continuous cost surface procedure ‘r.cost’ (Greenberg, Rueda, Hestir, Santos, & Ustin, 2011). This procedure uses a ‘friction’ coefficient. On the paved road network, we calibrated it with the distances obtained from the Malaysia Singapore association of drivers. We used a different friction for the pixels outside the paved road. We calibrated it from 96 samples, where we measured the distance of real mud tracks with Google maps tools (Samimi, Rahimi, Amini, & Jamshidi, 2019). We then identified a statistical correlation between crow-flight distance and track distances. We derived the off-road friction coefficient from it, and we applied it for all off-road transports in the workspace (Table 1). We used another GRASS procedure ‘r.mapcalc’ (Mitasova et al., 1995) to apply Malaysian transport costs equations to the distance maps. These equations give the transport cost as a function of transportation distance and tonnage of the truck (Table 2; Roda et al., 2012) which we obtained the transport cost maps as illustrated by Figure 1. In Figure 1, the darker colour is farther and more expensive, but the heterogeneity of the transport network plays a role too; where there is no transportation network the colour is very dark, and where there are various roads, the colour is lighter.

### 2.2 | Feedstock quantification

We separated feedstocks into primary sources and secondary sources of lignocellulosic biomass (Seixas, 2008). The primary sources are the harvesting biomass potentially available on the field. These biomasses are forest logging wastes, rubberwood logging wastes, oil palm fronds (OPF), oil palm trunks (OPT), and rice straw. The secondary sources are processing residues potentially available at mills. These biomasses are rice husk, sawmill and plywood mill waste, empty

Friction	Coefficient	SE	df	R <sup>2</sup>
Paved-road friction	0.07 km/pixel	0.0005	31	.9989
Off-road tortuosity	2.085 km of track/km of crow-flight	0.94	95	.8188
Off-road friction	$2.085 \times 0.07 = 0.145$ km/pixel			

Note: The paved road friction is the ratio between the real-life road distance and the distance computed from the pixelized road. We computed this ratio with statistical correlation between the official road distance of Malaysia and our GIS workspace.

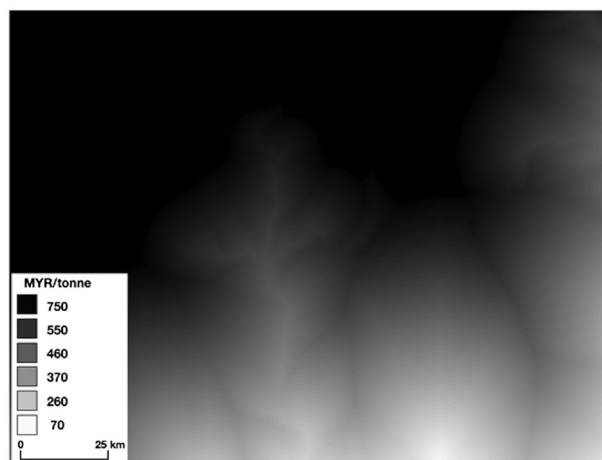
The off-road friction is the ratio between the real-life distances on off-road tracks and the crow-flight distance, computed from the pixel distances (knight's move algorithm). The ratio is obtained from a real sample of forest tracks where we measured the real tortuosity and real distances for 96 tracks.

**TABLE 2** Trucking cost equation of four sizes in Peninsular Malaysia

Truck size (tonnes)	Transport cost linear equation
1	MYR/tonne = distance (km) $\times$ 1.88657771 + 132.004442
3	MYR/tonne = distance (km) $\times$ 0.672738734 + 69.0615618
10	MYR/tonne = distance (km) $\times$ 0.258860505 + 49.3286760
26	MYR/tonne = distance (km) $\times$ 0.193541212 + 39.5358461

Note: The linear equations are fitted from data collected from logistic companies in Malaysia.

Source: Roda et al. (2012).



**FIGURE 1** This illustrative raster shows what would be the cost to reach any pixel from a given point (here cost for 1-tonne truck)

fruit bunches (EFB), and palm pressed fibre (PPF). We used the quantities of biomass published for Peninsular Malaysia (Roda et al., 2015; see Table 3). To explore the quantities of feedstock available per area in a raster workspace, we created a variable 'biomass yield'. For the primary sources, the national average quantity per pixel was quantified. For the

**TABLE 1** Friction coefficients

**TABLE 3** Biomass wastes availability in Peninsular Malaysia

	Total biomass availability <sup>a</sup>		Local biomass yield
	Min	Max	Tonne ha <sup>-1</sup> year <sup>-1</sup> (fresh)
<b>Lignocellulosic biomass wastes</b>	Million tonne/year (fresh)		
Primary sources			
Forest logging waste	1.83	2.65	0.44
Oil palm frond	7.12*		2.68
Oil palm trunk	17.80*		6.7
Rice straw	2.83	4.96	16.45
Rubberwood logging waste	0.20	0.70	0.64
Secondary sources			
Rice husk	0.51	0.67	65,555.56
Empty fruit bunch	9.40*		95,918.37
Palm pressed fibre	5.70*		58,163.27
Plywood mill waste	0.17	2.49	2,871.75
Saw mill waste	0.97	1.16	840.61

\*Probable quantity.

<sup>a</sup>Source: Roda et al. (2015).

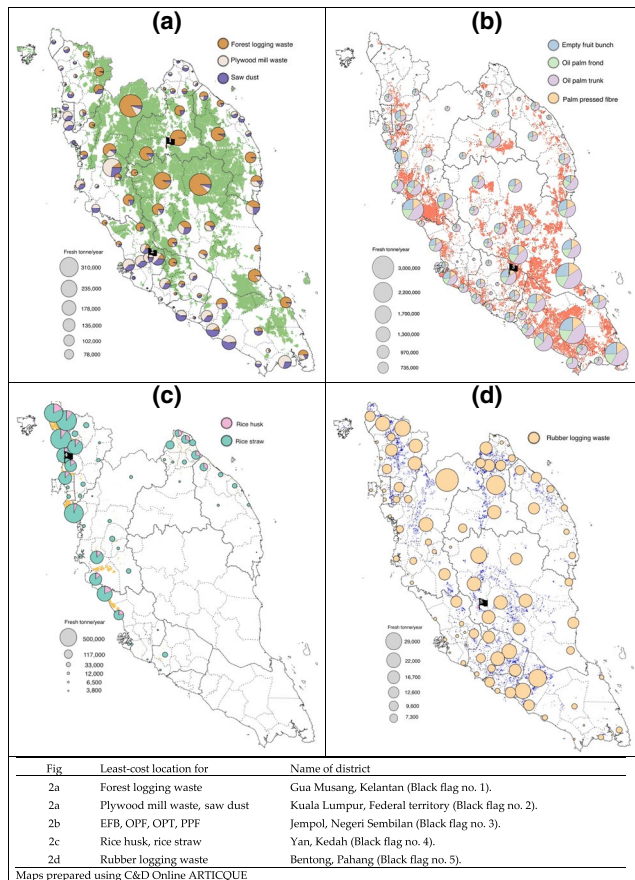
secondary sources, the same was applied into average quantity available per mill, or per pixel representing such mill. Table 4 shows the steps to derive these values. Malaysia is an equatorial country with limited seasonality. Except for rice which is harvested twice a year, all feedstocks are produced all year long. To simplify, we consider only annual production.

## 2.3 | Biomass transport simulation and least-cost location

Transportation of biomass was obtained through the multiplication of transport cost maps with waste density maps. This

**TABLE 4** Equations used to quantify biomass waste yield to tonne pixel<sup>-1</sup> year<sup>-1</sup>

	Equations	Unit
Step 1	Area per pixel = Total land use area of biomass/Total pixel cells of biomass	ha/pixel
Step 2	Average annual waste yield per hectare = Average of annual waste available/Total land use area of biomass	Tonne ha <sup>-1</sup> year <sup>-1</sup>
Step 3	Biomass availability = Average annual waste yield per area × Area of biomass per pixel	Tonne pixel <sup>-1</sup> year <sup>-1</sup>

**FIGURE 2** Land use, amount of biomass by districts, and least-cost locations in Peninsular Malaysia

procedure simulates the truck delivery of biomass contained in each pixel to the potential biorefinery location. Each pixel of the new map contained the biomass transport cost from that pixel to the biorefinery location in MYR/pixel. The sum of the values of each pixel under a given biomass category provides the total biomass transport cost to one specific location. With the GRASS procedure 'r.report' (Mitasova et al., 1995), the total biomass transport cost of each biomass to each district was computed. For each biomass, the district with the lowest total transport cost was identified as the best possible biorefinery mill location, and we named it 'least-cost location'. Several biomasses coming from the same crop (such as rice biomasses or palm biomasses) share the same least-cost location (Figure 2). We also created different sourcing

scenarios based on the least-cost locations as illustrated in the discussion.

## 2.4 | Data extraction and quantification of biomass transport cost

We created zonal maps based on general transport cost maps of each least-cost location using the GRASS procedure 'r.reclass' and each zone categorized by intervals of MYR50. The areas without biomass were nullified with the GRASS procedure 'r.null' and only areas with biomass were accounted. With the GRASS procedure 'r.univar' and the zonal map as inputs, we extracted the sum of biomass transport cost and the sum of biomass tonnage within each zone. These data were then calculated using Equation (1):

$$\text{Biomass supply cost}_{L,B} \frac{\text{MYR}}{\text{fresh tonne}} = \sum_{i=1}^z \frac{\text{BTC}_z}{\text{Tonnage}_z}, \quad (1)$$

where L denotes the location of the biorefinery, B denotes the types of biomass waste, z denotes the number of the zone, BTC denotes biomass transport cost of each zone and Tonnage denotes the amount of biomass waste in each zone.

The cost was converted from MYR into USD at the rate of 3.94 MYR/USD (Accountant General's Department of Malaysia, 2016). The marginal cost curves of the best potential mill location for each biomass category, using 1- and 26-tonne trucks, are established and used in the discussion.

## 2.5 | Landscape structure metric as spatial fragmentation index

The landscape structure is the arrangement of and relations between the parts or elements of the land mosaic, and can be described through landscape metrics. To investigate the linkages between spatial fragmentation and biomass transport cost, we needed to measure the spatial fragmentation (Rodrigue, Comtois, & Slack, 2013)



**TABLE 5** Equations of the selected landscape metrics

Edge density = $\frac{\sum_{k=1}^n e_{ik}}{A}$ (10,000)	(2)	<p><math>k</math> = patch type. It refers to the disjointed land areas (or patches) of a biomass category.</p> <p><math>n</math> = number of edge segments of patch type <math>k</math>. The edge segments are the pixels recognized as the border of the patches of a biomass category.</p> <p><math>e_{ik}</math> = total edge length (m) in landscape involving patch type <math>k</math>. For a biomass category, <math>k</math>, <math>e_{ik}</math> is the sum of edge length for all the patches of <math>k</math>.</p> <p><math>A</math> = total landscape area (<math>m^2</math>). It refers to the land cover of the study area, in our case, Peninsular Malaysia.</p> <p>Unit: metres per hectare</p>
Patch density = $\frac{N_{\text{patch}}}{A}$	(3)	<p><math>N_{\text{patch}}</math> = number of patches. It counts the total number of disjointed land area (or patches) for a biomass category.</p> <p><math>A</math> = sampling area size. This refers to our study area – Peninsular Malaysia.</p> <p>Units: Number of patches per square kilometre</p>
Aggregation index = $\begin{cases} \frac{G_i - P_i}{1 - P_i} & \text{for } G_i \geq P_i \\ \frac{G_i - P_i}{1 - P_i} & \text{for } G_i < P_i; P_i \geq .5 \\ \frac{G_i - P_i}{0 - P_i} & \text{for } G_i < P_i; P_i < .5 \end{cases}$ with $G_i = \left( \frac{g_{ii}}{\sum_{k=1}^n g_{ik}} \right)$	(4)	<p>Procedure: double-count method ‘Clumpy’ from software ‘Fragstats 4.2’.</p> <p><math>g_{ii}</math> = number of like adjacencies (joins) between pixels of land cover type (class) <math>i</math>.</p> <p><math>g_{ik}</math> = number of adjacencies (joins) between pixels of land cover types (classes) <math>i</math> and <math>k</math>. (<math>k</math> = unlike cell adjacencies)</p> <p>Each pixel is referred as a function of its neighbours, with neighbour <math>i</math> being a pixel of land cover that belongs to the biomass category <math>i</math>, and neighbour <math>k</math> being a pixel of land cover that does not belong to the biomass category <math>i</math>.</p> <p><math>P_i</math> = proportion of the landscape occupied by land cover type (class) <math>i</math>. It is the number of pixels for land cover of the biomass category <math>i</math> divided by the number of pixels of the study area (Peninsular Malaysia).</p> <p>Range: <math>-1 \leq \text{Aggregation index} \leq 1</math>.</p>

Note: Interpretation: Edge density and Patch density: a higher value indicates a more fragmented spatial structure.

Aggregation index: The value is expressed in dimension-less unit, from  $-1$  to  $1$ .  $-1$  is the most disaggregated state where each patch is one isolated pixel, and  $1$  is the most aggregated state where there is only one patch grouping all pixels of a biomass category.

**TABLE 6** Spatial fragmentation metrics for biomass in Peninsular Malaysia

Category of wastes	Biomass wastes	Spatial fragmentation metrics		
		Edge density (m/ha)	Patch density (no. of patches per sq km)	Aggregation index (procedure ‘Clumpy’)
From the field	Forest logging wastes	3.2705	0.0064	0.9804
	Oil palm frond (OPF)	6.0825	0.0610	0.9434
	Oil palm trunk (OPT)	6.0825	0.0610	0.9434
	Rice straw	1.1346	0.0341	0.9243
	Rubberwood logging wastes	11.7165	2.1068	0.6407
From mills	Empty fruit bunch (EFB)	0.2822	0.0034	0.6722
	Palm pressed fibre (PPF)	0.2822	0.0034	0.6722
	EFB and PPF	0.2822	0.0034	0.6722
	Plywood and Saw mill	0.3425	0.0261	0.6757
	Plywood mill	0.2990	0.0097	0.6794
	Rice husk	0.2780	0.0018	0.7169
	Saw dust	0.3364	0.0240	0.6725
From both	OPF & OPT and EFB & PPF	6.0847	0.0618	0.9434
	Rice straw and husk	1.1349	0.0342	0.9243

of land cover for biomass waste in Peninsular Malaysia. Many landscape metrics exist (Cardille & Turner, 2017; Haines-Young & Chopping, 1996). Among these metrics, ‘edge density’, ‘patch density’, and the ‘aggregation index’ express various aspects of the spatial

fragmentation, respectively, expressed by Equations (2), (3), and (4) in Table 5 (GRASS Development Team, 2019; McGarigal, Cushman, & Ene, 2012). The metrics for each biomass category was computed (see Table 6).

## 2.6 | Regression modelling and variables included

We performed a series of regression analyses to understand how to best describe biomass supply costs at any point of the country, according to different combinations (linear and nonlinear) of the factors. These factors are the transportation distance in km ( $\Delta$ ), the truck size in tonne ( $\theta$ ), the yield of wastes in tonne/ha ( $\xi$ ), the spatial fragmentation under the form of edge density of the feedstock in m/ha ( $\alpha$ ), or its patch density in number of patches/km<sup>2</sup> ( $\beta$ ), or its aggregation index ( $\gamma$ ), and also the categorical origin of the agricultural or forestry wastes ( $\omega$ ). In all, 19 models were analysed and compared (see Table 7). Their replicable equations are given in methodological annex (Annex A) under the form of R code. These 19 models are not predictive models which require validation. They are descriptive models meant to explore which structure and combination of variables best describe the observed biomass transportation cost in Peninsular Malaysia. The best way to assess these models is their Akaike information criterion (AIC) and their parsimony. However, in the future, other research should ideally validate the generality of their structures by exploring their behaviour in other countries.

## 3 | RESULTS

The first group of models (M1, M2, M3, M4a, M4b, M4c, M6a, M6b, and M6c) presents low adjusted coefficients of determination below 0.87, and relative standard errors above 22. None of them has simultaneously all the factors (distance, truck size, waste yield, fragmentation, and origin of wastes) in their structure. This suggests that all of these factors have their critical importance in the determination of the supply costs and should be included in the models.

The second group of models (M5, M7a, M7b, M7c, M8a, M8b, M8c, M9a, M9b, and M9c) presents higher coefficients of determination and lower relative standard errors. But a number of them are less robust, with non-significant parameters (M7a, M7b, M7c, and M8a), or with less significant parameters (M8b, M8c, M9b, and M9c), suggesting that their specific combinations of the factors are not the best representation of the reality.

The two best models are M5 and M9a. M9a = f(Distance, ln(Truck), Edge density, Waste origin) has the highest adjusted coefficient of determination and the lowest relative standard error among these 19 models. The model M5 has satisfying performances while not describing any aspect of the fragmentation factor: this could mean, according to the

**TABLE 7** Model selection to describe biomass supply cost

Model	$\Delta$	$\theta$	$\ln(\theta)$	$\xi$	$\ln(\xi)$	$\alpha$	$\beta$	$\gamma$	$\omega$	Adj. $R^2$	RSE	df	AIC
M1	$\Delta, \theta$	0	0							.641	36.95	1,218	12,274
M2	$\Delta, \ln(\theta)$	0	0							.667	35.60	1,218	12,183
M3	$\Delta, \ln(\theta), \xi$	0	0	0						.682	34.81	1,217	12,129
M4a	$\Delta, \ln(\theta), \alpha$	0	0			0				.698	33.89	1,217	12,063
M4b	$\Delta, \ln(\theta), \beta$	0	0				0			.677	35.08	1,217	12,148
M4c	$\Delta, \ln(\theta), \gamma$	0	0					0		.856	23.44	1,217	11,164
M5	$\Delta, \ln(\theta), \omega$	0	0						0	.896	19.86	1,215	10,762
M6a	$\Delta, \ln(\theta), \xi, \alpha$	0	0	0		0				.729	32.11	1,216	11,933
M6b	$\Delta, \ln(\theta), \xi, \beta$	0	0	0			0			.694	34.11	1,216	12,080
M6c	$\Delta, \ln(\theta), \xi, \gamma$	0	0	0				0		.865	22.69	1,216	11,085
M7a	$\Delta, \ln(\theta), \xi, \alpha, \omega$	0	0	ns		0			0	.898	19.70	1,213	10,744
M7b	$\Delta, \ln(\theta), \xi, \beta, \omega$	0	0	ns			0.001		0	.897	19.82	1,213	10,758
M7c	$\Delta, \ln(\theta), \xi, \gamma, \omega$	0	0	ns				0.01	0	.897	19.83	1,213	10,760
M8a	$\Delta, \ln(\theta), \ln(\xi), \alpha$	0	0		ns	0			0	.898	19.69	1,213	10,743
M8b	$\Delta, \ln(\theta), \ln(\xi), \beta$	0	0		0.005		0.01		0	.897	19.79	1,213	10,754
M8c	$\Delta, \ln(\theta), \ln(\xi), \gamma$	0	0		0.01			0.01	0	.897	19.80	1,213	10,756
M9a	$\Delta, \ln(\theta), \alpha, \omega$	0	0			0			0	.898	19.69	1,214	10,742
M9b	$\Delta, \ln(\theta), \beta, \omega$	0	0				0.001		0	.897	19.81	1,214	10,756
M9c	$\Delta, \ln(\theta), \gamma, \omega$	0	0					0.01	0	.897	19.83	1,214	10,759

Note:  $\Delta$ , distance;  $\theta$ , truck;  $\xi$ , biomass yield;  $\alpha$ , edge density;  $\beta$ , patch density;  $\gamma$ , aggregation index;  $\omega$ , waste origin; it is a categorical variable that either take the value of 'field', 'mill', or 'both'. ns, non-significant.

rule of parsimony, that this fragmentation factor is not needed to understand the structure of the costs. However, the AIC is lower in the case of M9a. This confirms that the fragmentation factor has critical importance too, and needs to be included and better understood. Thus, the model M9a describes best the structure of the biomass supply costs in Peninsular Malaysia. Table 8 provides its details and its reliability.

We find that the base supply cost is higher for the biomass wastes originating from the mills (69.67 USD/tonne) than for the wastes originating from the fields (63 USD/tonne). This could contradict the intuition because mills produce proportionally much more wastes per hectare. The fact that the mills are relatively small in average, and are scattered all over the territory, is the reason for the counterintuitive finding.

We find also that the fragmentation (edge density) of the resource is extremely costly: A 1 million hectare feedstock would see an increase of 4.16 USD/tonne for every added unit of edge density. With a similar edge density as paddy fields, the field size of such a feedstock would be of 950 ha in average and have a baseline supply cost of 67.16 USD/tonne.

The same feedstock with an edge density similar to palm oil plantations would have field size of 26 ha in average, inducing a surplus of 20.8 USD/tonne for the supply cost. And with an edge density similar to rubber plantations, field size would be of 7.8 ha in average, inducing another surplus of 20.8 USD/tonne for the supply cost compared to oil palm plantations.

The supply cost also increases in average by 6.78 USD/tonne for every added 100 km of transportation distance. Conversely and compared to a 1-tonne truck, the supply cost logarithmically decreases according to the tonnage, with −36 USD for a 3-tonne truck, and with −84 USD for a 26-tonne truck.

The scattered nature of the mills increases the supply cost, despite the relatively high concentration of wastes in each mill. This unexpected finding raises the question of whether this model separates correctly the fragmentation from the biomass yield. The categorical variable 'waste origin' implicitly contains information on the concentration of biomass yield per hectare since the yields are immensely more concentrated in a mill than in fields. It also contains information on spatial fragmentation since most of the mills are scattered over the territory, which makes them

**Model M9a: USD/fresh tonne =  $\Delta + \ln(\theta) + \alpha + \omega$**

Parameter	Coefficient estimate	SE	t value	Pr(> t )
$\Delta$ : Transportation distance	0.0678	0.002915	23.274	<2e-16***
$\ln(\theta)$ : $\ln(\text{truck size})$	−26.07	0.458950	−56.805	<2e-16***
$\alpha$ : Fragmentation (edge density)	1.066	0.228711	4.662	0.00000348***
$\omega$ : Waste origin_field	63.06	1.974433	31.937	<2e-16***
$\omega$ : Waste origin_mill	69.67	1.451147	48.009	<2e-16***
$\omega$ : Waste origin_both	62.35	2.027559	30.750	<2e-16***

Note: Residual SE: 19.69 on 1,214 df.

Multiple  $R^2$ : .8986, Adjusted  $R^2$ : .8981.

F statistic: 1,792 on 6 and 1,214 df,  $p < 2.2\text{e-}16$ .

Significance codes: \*\*\*0; \*\*0.001; \*0.01.

**TABLE 8** Biomass supply cost as a function of transportation distance, truck size, fragmentation, and waste origin

**Model M6a: USD/fresh tonne =  $\Delta + \ln(\theta) + \alpha + \xi$**

Parameter	Coefficient estimate	SE	t value	Pr(> t )
$\Delta$ : Transportation distance	0.14624175	0.00376956	38.8	<2e-16***
$\ln(\theta)$ : $\ln(\text{truck size})$	−15.54994379	0.64271174	−24.19	<2e-16***
$\alpha$ : Fragmentation (edge density)	3.81978851	0.26104091	14.63	<2e-16***
$\xi$ : Biomass yield	0.00038155	0.00003234	11.8	<2e-16***

Note: Residual SE: 32.11 on 1,216 df.

Multiple  $R^2$ : .7299, Adjusted  $R^2$ : .729

F-statistic: 821.4 on 4 and 1,216 df,  $p < 2.2\text{e-}16$ .

Significance codes: \*\*\*0; \*\*0.001; \*0.01.

**TABLE 9** Biomass supply cost as a function of transportation distance, truck size, fragmentation, and biomass yield

inherently a fragmented source of biomass. The examination of models M7a and M6a which differ from model M9a by only one variable, allows to clarify this point. Model 7a is the same as M9a plus a variable on describing the concentration of biomass yield per hectare. But this variable is not significant (see Table 7). In model M6a, the categorical waste origin is replaced by the biomass yield (see Table 9). It reinforces the apparent weight of the fragmentation, which is three times more influential on the cost structure. The truck size influence is lower but remains a crucial factor, and the influence of the transportation distance importance is more than double. The yield of biomass, although being significant, induces little supply cost variation. Altogether these results demonstrate that the categorical variable 'waste origin' encapsulates relatively few information on the concentration of yield per hectare, and more on fragmentation. However, the regimes of fragmentation of fields and mills are so different that they are not appropriately described by a single variable, as it is the case in model M6a. They are better described by the categorical variable 'waste origin'. The relationships of the fragmentation to the supply costs according to the origin of the wastes would probably yield interesting results with nonlinear models, but it is beyond the scope of this paper.

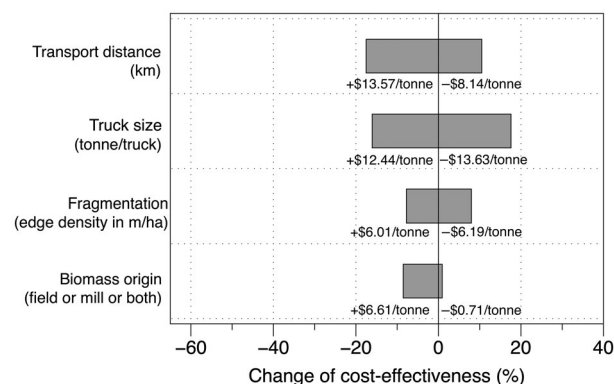
## 4 | DISCUSSION

### 4.1 | Respective impacts of supply cost factors

In a tropical country such as Malaysia, the biomass feedstocks are heterogeneous and fragmented. The increase in biomass supply cost with spatial fragmentation demonstrates that landscape structure can be as much critical for biorefinery economics, as transport distances are (Ghaffariyan, Acuna, & Brown, 2013; Reeb, Hays, Venditti, Gonzalez, & Kelley, 2014; Tahvanainen & Anttila, 2011; Vijay Ramamurthi, Cristina Fernandes, Sieverts Nielsen, & Pedro Nunes, 2014). Our results are the first to quantify the direct effect of landscape structure on the transport cost. The fragmentation amplifies the average transportation distance. This consequently amplifies nonlinearly the effects of the size of the fleet trucks. The respective impact of each factor can be measured with the model M9a, and can be visualized by comparing to a base scenario attainable for all feedstocks, of best and worst scenarios, in

Table 10 and Figure 3. The baseline scenario is set at 1 million tonnes of biomass supply because this quantity is commonly available from almost all Malaysian feedstocks. We assign to it the fragmentation of the most common feedstock (oil palm wastes). The most common trucks used for agriculture and biomass transport in West Malaysia are 3-tonne trucks. 26-tonne trucks are uncommon because this kind of trucks cannot reach most of the fields. The best truck scenario is set at 10-tonne truck and the worst with 1-tonne truck. The average distances are computed by GIS for the baseline, best and worst scenarios for 1 million tonnes of supply.

Among all the cost factors, the landscape fragmentation is a heritage of geography, history, and long-term agricultural policies. Biomass entrepreneurs cannot modify this fragmentation, but they can act on the truck size factor. For example, in the United States & EU, the trucks used for biomass are always above 20 tonnes (Laitila, Asikainen, & Ranta, 2016; Sosa & McDonnell, 2015; Teter et al., 2017). In Malaysia, 98.5% of businesses are very small (Department of Statistics Malaysia, 2017) and are extremely small if compared to European standards (Gonzales, Hommes, & Mirmulstein, 2019). In general, 48% of truck traffics are light-weighted truck, 33% and 19% are medium and heavy-weighted truck respectively (see Table 11; Ministry of Transport Malaysia, 2019). In the agriculture and forestry sector, the most common trucks are 1-tonne trucks, while 10- to 12-tonne trucks were used only by big mills (Roda et al., 2015).



**FIGURE 3** Impact of the main biomass supply cost factors in Peninsular Malaysia. The baseline scenario is centred at 0%. The cost-effectiveness increases when biomass supply costs decrease

**TABLE 10** Supply scenarios in Peninsular Malaysia

Parameter	Unit	Scenarios		
		Best	Baseline	Worst
Transport distance	km	180	300	500
Truck size	tonne	10	3	1
Fragmentation (edge density)	m/ha	11.7165	6.0825	0.278
Biomass origin	categories	62.347859	63.056592	69.66853



**TABLE 11** Five-year average (2013–2017) of truck traffic composition at 14 selected stations

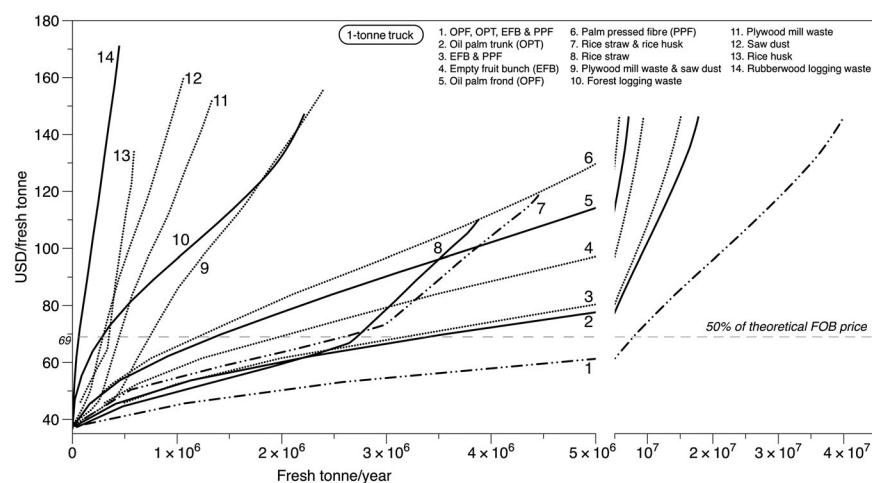
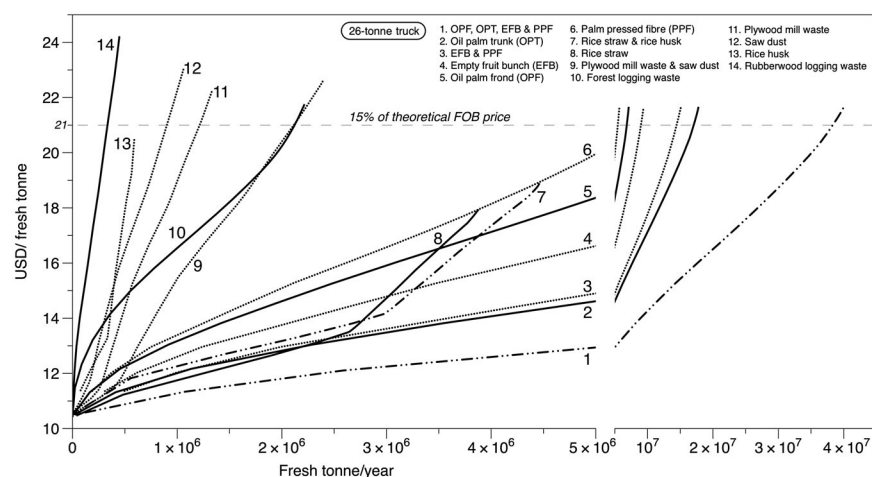
Light truck	Medium truck	Heavy truck
Below 2 tonnes	2–10 tonnes	Above 10 tonnes
48	33	19

Source: Ministry of Transport Malaysia (2019).

## 4.2 | International competitiveness of Malaysian biomass

One criterion to assess the feasibility of any industry willing to use Malaysian biomass would be to compare its local cost with the price or cost of biomass available on the international market. For example, we can compare with the feedstock biomass costs in the United States or the densified biomass costs exported by the United States on the international market, Free On Board cost (U.S. Energy Information Administration, 2020). We estimated a theoretical fresh biomass FOB price based on Mani, Sokhansanj, and Turhollow (2006) and Mani (2005) as a benchmark for 'theoretical FOB price' (FOB export cost – densification cost).

Compared to the marginal cost curves of the best potential mill location for each biomass category (Figures 4 and 5; Annex B), this kind of competitiveness benchmark discriminates three groups of Malaysian feedstocks. These groups are critical for the scale of the possible biorefineries, and for the choice of biofuel technologies. Wastes from plywood and sawmills, forest logging, plywood mills, rubberwood logging, sawdust, and rice husk belong to the first group. They could only supply much less than 1 million fresh tonnes/year at 50% of the international benchmark if transported with 1-tonne trucks (Figure 4). However, they could supply the total of their available wastes if transported with 26-tonne trucks (Figure 5). In the case of the forest logging wastes, 26-tonne trucks access to most of the forest tracks is hypothetical in actual Malaysian logistic conditions. The second group is much more competitive. These wastes are OPT, EFB, OPF, PPF, EFB + PPF, rice straw, and rice straw + rice husk. They could supply from 1.2 to 3.5 million fresh tonnes/year at 50% of the international benchmark with 1-tonne trucks (Figure 4), and from 5.4 to 17 million fresh tonnes/year at 15% of the international benchmark with 26-tonne trucks (Figure 5). The third

**FIGURE 4** Marginal supply cost curves of Malaysian fresh feedstocks: 1-tonne truck, with international benchmark**FIGURE 5** Marginal supply cost curves of Malaysian fresh feedstocks: 26-tonne truck, with international benchmark

group, the simultaneous collection of all lignocellulosic wastes from oil palm plantation or oil palm mills, is extremely competitive. It can supply 8.2 million fresh tonnes/year at 50% of the international benchmark with 1-tonne trucks (about 20% of Malaysian oil palm wastes, Figure 4), and 38 million fresh tonnes/year at 15% of the international benchmark with 26-tonne trucks (about 97% of Malaysian oil palm wastes Figure 5). The specificity of this third group is that it mixes wastes from the fields and wastes from the mills. It implies that the mills could be used as collection and pre-treatment point since they are already the collection points of the Fresh Fruit Bunches. In these conditions, nothing would prevent to add pre-treatment stages to dry and densify the biomass prior to further transportation.

### 4.3 | Feasibility of consolidation, collection, and pre-treatment of the biomass

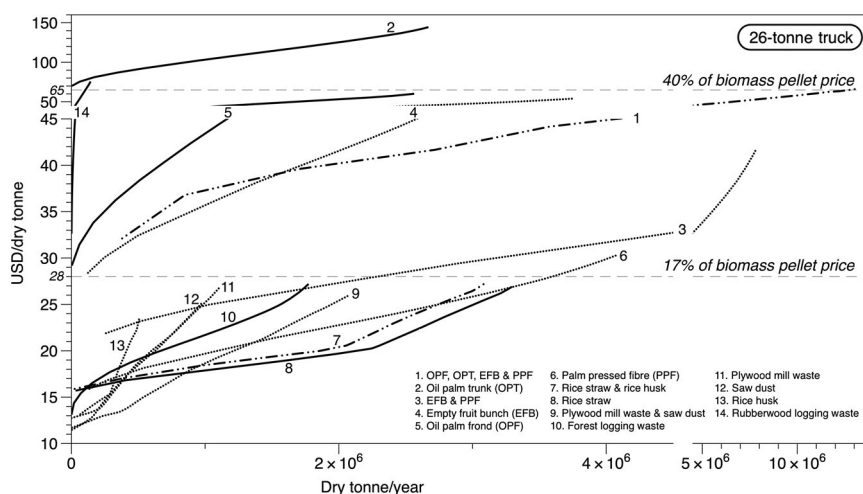
In the hot and humid Malaysian weather, the actual practice is to transport quickly the biomass in fresh matter, to avoid microbial degradation (Chico-Santamarta et al., 2011; Hess, Wright, & Kenney, 2007; Larson et al., 2015; Rentizelas, Tolis, & Tatsiopoulou, 2009; Salètes, Caliman, & Raham, 2004). The low bulk density and the high moisture content (see Annex C) of most of the biomass reduce the profitability of feedstock transportation. Since 26-tonne trucks cannot access many of the tracks within the field (Roda et al., 2015; Shafie, Masjuki, & Mahlia, 2014; Yusoff, 2019), collection points would be needed for their large-scale use. The exact cost of such facilities is beyond the scope of the present paper, but an approximation of their supply cost can be assessed against international benchmarks (we omit the densification cost in Malaysia). We use international FOB biomass pellet prices (USD162/tonne; U.S. Energy Information Administration, 2020) as a benchmark for the supply of dry feedstocks. We consider only the transportation by 26-tonne

trucks that would make sense with densification facilities. Three different dry feedstocks emerge (see Figure 6). OPT and rubberwood logging wastes which the fresh feedstocks with the highest water content (Annex C). They form the first group with either very little dry matter available or most of it above 40% of the international FOB price for pellets. The other oil palm wastes except for PPF (and OPT) form the second group, with most or all of their dry feedstock above 17% of the international benchmark.

All the remaining wastes form the third group, with 100% (or almost) of the dry feedstock below 17% of the international benchmark. The most remarkable and the cheapest among them are the wastes from plywood and sawmills (0.2–0.8 million dry tonnes/year), and rice straw (0.8–3.3 million dry tonnes/year).

### 4.4 | Policy implications

Altogether, these considerations have strong implications for policymakers: the importance of the landscape structure may make a seemingly abundant biomass not viable for biorefineries if too fragmented, while a much less abundant one, but more concentrated may be viable. This first implies that with proper supply chain management and location optimization, Peninsular Malaysia biomass could supply a competitive bio-fuel industry. There are enough quantities to sustain small or medium mono-feedstock industries if their location is carefully chosen. This also means that biomass studies in Malaysia and countries with similar conditions should consider the design and location of collection consolidation and pre-processing, and hubs to connect small and medium stakeholders with bigger ones. The overall results of this study have also shown that large multi-feedstock industries can be economically viable. This means that in Malaysia and other tropical countries where the landscape is typically very fragmented, multi-crop feedstocks could be considered for sustainable biorefineries. It



**FIGURE 6** Marginal supply cost curves of Malaysian dry feedstocks: 26-tonne truck, with international benchmark

poses new technological and economic implications, but these are beyond the scope of the present paper.

## 5 | CONCLUSION

Fragmentation of the landscape is costly in tropical countries with complex mosaics of land uses, such as Malaysia. The feedstock cost increases by more than 4 USD/tonne for every added unit of edge density. In comparison, it increases by more than 6 USD/tonne, but by every 100 km of added average transport distance. These natural drawbacks could be offset by organizing better logistic chains. From a fleet of 1-tonne trucks, the cost decreases by −36 USD/tonne if using 3-tonne trucks, and down to −84 USD/tonne if using 26-tonne trucks. But most of the biorefinery technologies and solutions for agricultural and forestry wastes were developed in the rather uniform plains of North Europe and North America. Our results mean that these technologies and solutions cannot be just transferred to tropical countries with complex landscape mosaics. We demonstrated here how the landscape structure, through the concept of fragmentation, is a major determinant of biomass economics under the tropics. For policymakers, counterintuitive situations may arise, such as seemingly abundant biomasses may be less profitable if too fragmented while much less abundant but more concentrated biomasses may be more efficient. There may be other situations where multi-crop biomass strategies are more profitable than relying on too fragmented feedstocks. The concept of landscape fragmentation has been mostly used in ecology, for edge effects and other phenomenon. But our results suggest that fragmentation of the landscape probably influences the economics of many activities dealing with agriculture and forest resources, too. Methodologically, it would be interesting to develop fragmentation metrics specifically designed to capture economic aspects. Conceptually, it would also be interesting to explore how multifactorial dynamics, such as deforestation, are linked to pre-existing fragmentation and change it.

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## AUTHORS' CONTRIBUTIONS

C.O. and G.D. designed, planned and carried out the GIS model and simulation. J.-E.H. designed template for data extraction and collation. C.O. and J.-M.R. performed the statistical modelling, analytic calculations, interpretation of the results and co-wrote the manuscript. J.-E.H., M.O.S.H., N.K., A.R.A., and A.N.A.M. provided feedback and helped shape

the research, analysis, and manuscript. J.-M.R. conceived the original idea, verified the models and simulations, and was in charge of overall direction and planning.

## DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in CIRAD Dataverse at <https://dataverse.cirad.fr/dataset.xhtml?persistentId=doi:10.18167/DVN1/IQO4L6>.

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## SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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